Deep Space Network Antenna Monitoring using Adaptive Time Series Methods and Hidden Markov Models

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1 Background and Introduction

The Deep Space Network (DSN) (designed and operated by the Jet Propulsion Laboratory for the National Aeronautics and Space Administration (NASA)) provides end-to-end telecommunication capabilities between earth and various interplanetary spacecraft throughout the solar system. Since spacecraft are always severely limited in terms of available transmitter power (for example, each of the Voyager spacecraft only use 20 watts to transmit signals back to earth), all subsystems of the end-to-end communications link (radio telemetry, coding, receivers, amplifiers) tend to be pushed to the absolute limits of performance. The large steerable ground antennas (70m and 34m dishes) represent critical potential single points of failure in the network. In particular there is only a single 70m antenna at each complex because of the large cost and calibration effort involved in constructing and operating a steerable antenna of that size. The 70m antennas were originally built in the 1960's and are now operating beyond their originally designed working lifetime. Hence, as antenna components age and become less reliable, there is significant motivation to monitor antenna signals online in order to quickly detect potentially catastrophic failures and to identify trends which show gradual component degradation over time. In this paper we describe recent results in the development of robust online monitoring algorithms. These algorithms are based on a hybrid combination of time series modelling, pattern recognition, and hidden Markov model methods.

2 DSN Antenna Systems

The DSN antenna pointing systems consist of azimuth and elevation axes drives which respond to computer-generated trajectory commands to steer the antenna in real-time. Pointing accuracy requirements for the antenna are such that there is little tolerance for component degradation. Achieving the necessary degree of positional accuracy is rendered difficult by various non-linearities in the gear and motor elements and environmental disturbances such as gusts of wind affecting the antenna dish structure. Off-beam pointing can result in rapid fall-off in signal-to-noise ratios and consequent potential loss of irrecoverable scientific data from the spacecraft.

The antenna servo pointing systems are a complex mix of electro-mechanical components. A faulty component manifests itself indirectly via a change in the characteristics of observed sensor readings in the pointing control loop. Because of the non-linearity and feedback present, direct causal relationships between fault conditions and observed symptoms can be difficult to establish — this makes manual fault diagnosis a slow and expensive process. In addition, if a pointing problem occurs while a spacecraft is being tracked, the antenna is often shut-down to prevent any potential damage to the structure and the track is transferred to another antenna if possible. Hence, at present, diagnosis often occurs after the fact when the original fault conditions are impossible to replicate, further hindering the troubleshooting process.

3 Time Series and Hidden Markov Models for Fault Detection

In this paper we describe the application of time series and Markov modelling methods to the problem of online detection of fault conditions in the antenna electro-mechanical drive systems. Conventional control-theoretic approaches to fault detection in dynamic systems rely heavily on accurate linear models of the system [1] and, hence, are not practical for our purposes due to the complexity and non-linearity of the antenna system. Knowledge-based approaches are not directly applicable either due to the dynamic nature of the system and the presence of signal feedback.

Instead we have developed an approach based on autoregressive exogenous (ARX) time series coefficients which are estimated online by treating the rate command and the drive motor current as the system input and output respectively. Faults are detected by observing changes in the ARX coefficients over time. This is achieved by the use of non-parametric statistical pattern recognition methods which estimate the posterior probability that the coefficients belong to particular states such as normal, transient faults, etc. [2]. Finally, temporal correlation is modelled at the state level by embedding the state probabilities within a hidden Markov model (HMM) framework [3].

The Markov nature of the model refers to the fact that the future state of the system is only governed by the present state and not the past (few the commonly used first-order model). While this may seem like a strong assumption it is in fact broadly applicable in practice - extensions to the basic idea (such as semi-Markov models for explicit state durations) allow the capture of more complicated model dynamics if required. The "hidden" aspect of the Markov model refers to the fact that while the underlying state of the system can not be directly observed (it is hidden from the observer), nonetheless symptoms (in this case the estimated ARX coefficients), which are a probabilistic function of the states, can be directly observed. Hence, by the use of maximum likelihood techniques, for a *given* sequence of observed coefficients, the most likely sequence of underlying states can be *inferred*.

The HMM method was primarily developed for modelling the dynamic non-stationary nature of speech signals - the application of the method to online monitoring of dynamic systems has only recently been proposed [4, 5]. The HMM approach is an extremely effective tool, allowing the incorporation via the model transition probabilities of relatively high-level knowledge regarding long-term system behaviour (such as MTBF estimates), and reducing the false alarm rate by several orders of magnitude (compared to no modelling at all of the temporal context of the problem).

4 Results and Conclusions

The application of the HMM method is illustrated using online field data from a 34m meter beam-waveguide research antenna located at the DSN Goldstone site in California. Empirical results based on online tests, where hardware faults were introduced into the system in a controlled manner, demonstrate the practical utility of the method: all faults were detected within a few seconds of occurrence and no false alarms were recorded during the entire test. Extensions of the basic method arc also discussed: the online adaptation of (lie model over time, the ability to detect novel fault conditions (such as transient behaviour) [6], and the ability to diagnose and isolate faults to the component level based on simplified system models.

The combination of time series, pattern recognition and Markov mode] methodologies provide a novel and robust framework for online monitoring of dynamic systems where more conventional methods are not app licable. In particular, other th an the fact that it is not directly amenable to linear modelling, there is nothing unique about the antenna application: in principle, the method could be applied to monitoring dynamic systems such as industrial machinery, chemical process plants, onboard vehicle systems, biomedical systems, and so fort]].

In conclusion, the current focus of the work is to extend to the experiments to the operational 70m antennas: in addition the HM M monitoring system is now included as part of the standard design of the next generation of DSN antennas which arc to be constructed and operational by the mid to late 1990's.

Acknowledgements

The research described in this paper was performed at the Jet Propulsion laboratory, California Institute of Technology, under a contract with the National Aeronautics and Space Administration and was supported in part by D ARPA under grant number AFOSR- 90- 0199 and the ONR by grant number N00014 92-J- 1860.

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